11. Wang Lai-jun, Shi Zhong-ke. The Implement of Genetic Algorithms in Departure Sequencing Problem[J]. Systems Engineering-theory & Practice, 2005, 24(09): 119-125. (in Chinese)
12. Zhang Qi-qian, Hu Ming-hua, Shi Sai-feng, et al. Optimization algorithm of flight take-off and landing on multi-runways[J]. Journal of Traffic and Transportation Engineering, 2012, 12(06): 63-68. (in Chinese)
13. Clare GL, Richards AG. Optimization of taxiway routing and runway scheduling[J]. IEEE Transactions on Intelligent Transportation Systems, 2011, 12(4): 1000-1013.
14. Solveling G, Solak S, Clarke J-P et al. Runway operations optimization in the presence of uncertainties[J]. Journal of Guidance, Control, and Dynamics. 2011, 34(5): 1373-1382.
15. Li Zhen, Zhang Jun, Zhang Xue-jun. Modeling and Simulation of Departure Scheduling Problem Based on Genetic Algorithm[J]. Tansportation and Computer, 2008, 26(06): 39-42. (in Chinese)
16. Mu Caihong. Co-evolutionary numerical optimization algorithms and their applications[D]. Xi'an: Xidian University, 2010. (in Chinese)
17. Liu J, Zhong W, Jiao L. An organizational evolutionary algorithm for numerical optimization[J]. IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, 2007, 37(4): 1052-1064.
18. Runarsson TP, Yao X. Stochastic ranking for constrained evolutionary optimization[J]. IEEE Transactions on Evolutionary Computation, 2000, 4(3): 284-294.

Improvement of Low Complexity Sparseness Controlled MPNLMS Algorithm Based on Sparse Impulse Response

Huanchang Qin, Zaiqun Wu

Department of Physics and Communication, Baise University, Baise, Guangxi, 533000, China

Corresponding author is Zaiqun Wu

Abstract
In the work, we obtained probability distribution of error signals with different confidence levels by Hampe censored estimation function. The data collection of "input-expectation" was divided into four data space where the ratios of data disturbed by impulse noise are different. The data space with small data ratio was calculated by SM-SCMPNLMS Algorithm. In data space with large data ratio, the computation complexity was reduced to solve steady-state problems because of pulse noise disturbance by restraining error signal amplitude and using larger error threshold. The effectiveness of this algorithm was proved by simulation.
Keywords: DATA SUBSPACE, SPARSENESS CONTROL, SET-MEMBERSHIP FILTERING, ECHO CANCELLATION

1. Introduction

Real-time voice communication causes increase of echo delay with sparse path. The convergence rate was proportional to coefficient sparseness. MPNLMS algorithm in References [1], [2] and [3] was used to update adaptive filter coefficients in network echo cancellation system. The convergence performance was affected by the adaptive filter coefficient sparseness. Therefore, the contradiction between convergence rate and calculation complexity cannot be solved.

In the work, we obtained probability distribution of error signals with different confidence levels by Hampe censored estimation function. After that, the data collection of "input-expectation" was divided into four data space where the ratios of data disturbed by impulse noise are different.The data space with small data ratio was calculated by SM-SCMPNLMS Algorithm. In data space with large data ratio, the computation complexity was reduced to solve steady-state problems because of pulse noise disturbance by restraining error signal amplitude and using larger error threshold. The effectiveness of this algorithm was proved by simulation.

2. SM-scmpnlms algorithm

In set-membership estimation algorithms, S denotes collection of "input-expectation" data pairs (x, d) in adaptive filter. When (x, d) belongs to S, then Θ will denote collection of coefficient vectors $w \in R^{N+1}$ where input error range is not more than threshold γ_1. H_k denotes collection of the whole w where input error range is not more than threshold γ_1 at k. As the constraint set of data pair (x, d) with hyperplane border, H_k is defined as follows.

$$H_k = \{w \in R^{N+1} : \left|d_k - w_k^T x_k\right| \le \gamma_1\} \quad (1)$$

Where xk and wk are input signal and coefficient vectors of filter at k (x_k=$[x_{0,k}\ x_{1,k} \cdots x_{L-1,k}]^T$, w_k=$[w_{0,k}\ w_{1,k} \cdots w_{L-1,k}]^T$); L is the order of filter; d_k system expectation signal at k.

$$d_k = x_k^T \varpi + n_k + v_k \quad (2)$$

Where ϖ is identified echo path; n_k additive white Gaussian noise; v_k impulsive noise.

In SM-SCMPNLMS algorithm, if $w_k \in H_k$, then w_k will not be updated. If $w_k \notin H_k$, then the following

constraint optimization criterion will be used for vector update.

$$\min \left\| w_{k+1} - w_k \right\|^2_{Q_{k+1}^{-1}} \quad (3)$$

The following constraint condition is satisfied.

$$d_k - x_k^T w_{k+1} = \gamma_1 \quad (4)$$

The Lagrange multiplier is used to solve the above optimization problems. After that, output error signal of filter at k is defined as follows.

$$e_k = d_k - x_k^T w_k \quad (5)$$

Then we obtain SM-SCMPNLMS coefficient update formula.

$$w_{k+1} = w_k + \frac{\alpha_0 Q_{k+1} x_k e_k}{\delta + x_k^T Q_{k+1} x_k} \quad (6)$$

Where α_0 is set-membership step.

$$\alpha_0 = \begin{cases} 1 - \gamma_1 / |e_k| & if\ |e_k| > \gamma_1 \\ 0 & else \end{cases} \quad (7)$$

Where $\gamma_1 = \sqrt{5}\sigma_n$; σ_n^2 is disturbance signal variance without impulse noise in system. In Equation (6), δ is regularization parameter. It is used to prevent a zero denominator from minimum input signal. In SM-SCMPNLMS coefficient update equation, Q_{k+1} is the step control matrix for filter coefficient assignment ($Q_{k+1} = diag\{q_{0,k+1}\ q_{1,k+1} \cdots q_{L-1,k+1}\}$). Diagonal elements in Q_{k+1} are calculated by the following recurrence relation.

$$q_{l,k+1} = \frac{[1 - 0.5\delta_k]}{L} + [1 + 0.5\delta_k] \frac{\xi_{l,k+1}}{\sum_{i=0}^{L-1} \xi_{i,k+1}} \quad (8)$$

$$\delta_k = \frac{L}{L - \sqrt{L}} \left[1 - \frac{\|w_k\|_1}{\sqrt{L}\|w_k\|_2} \right] \quad (9)$$

Where $\|w_k\|_p = \sqrt[p]{\sum_{i=0}^{L-1} |w_{i,k}|^p}$.

$$\xi_{l,k+1} = \max\left\{F(|w_{l,k}|), \tau \times \upsilon_{l,k+1}\right\} \quad (10)$$

Where τ is used to prevent parameter update stop from overlarge coefficient difference ($\tau = 1/L$ - $5/L$).

$$\upsilon_{l,k+1} = \max\left\{\eta, F(|w_{0,k}|), \cdots F(|w_{l,k}|), \cdots F(|w_{L-1,k}|)\right\} \quad (11)$$

where η is used to prevent algorithm freeze when the whole coefficients are 0 (η=0.01).

$$F(|w_{l,k}|) = In(1 + 1000 \times |w_{l,k}|) \quad (12)$$

3. Ism-scmpnlms

In traditional set-membership estimation algorithms, large pulse noise in system will cause sudden increase of e_k to make $e_k >> \gamma_1$ when filter converges tosteady state. Then coefficient update step α_0 is close to 1. Based on set-membership, filter coefficient will not update or update at little step when filter converges to steady state. Therefore, we use Hampe censored estimation function $\rho(\bullet)$ to restrain e_k in Equation (7), thus obtaining an improved SM-SCMPNLMS algorithm in the work. $\rho(\bullet)$ is defined as follows based on Reference [4].

$$\rho(e)=\begin{cases} e_k^2/2, & 0<|e_k|<\xi \\ \xi|e_k|-\xi^2/2, & \xi\le|e_k|<\Delta_1 \\ \frac{\xi(\Delta_1+\Delta_2)-\xi^2}{2}+\frac{\xi}{2}\frac{(|e_k|-\Delta_2)^2}{\Delta_1-\Delta_2} & ,\ \Delta_1\le|e_k|<\Delta_2 \\ \frac{\xi}{2}(\Delta_1+\Delta_2)-\frac{\xi^2}{2}, & \Delta_2\le|e_k| \end{cases} \quad (13)$$

Where threshold parameters ξ, Δ_1 and Δ_2 affect restrain effect of algorithm to impulse noise. In impulse noise disturbance condition, the whole distribution of e_k is hardly to determine. However, it is assumed that e_k follows Gaussian distribution based on additive impulsive noise. Its variation can be obtained by estimation. The probability will be denoted as follows when $|e_k|$ is larger than certain threshold T.

$$\theta_T(k)=P\{|e_k|>T\}=1-erf\left(\frac{T}{\sqrt{2}\sigma_{e,k}}\right) \quad (14)$$

Where erfc(τ) is error function ($erfc(\tau)=\frac{2}{\sqrt{\pi}}\int_0^\tau e_k^{-x^2}dx$); $\sigma_{e,k}^2$ error signal variation at k. error signal variation is updated by the methods in References [6] and [7].

$$\sigma_{e,k}^2=\lambda_e\sigma_{e,k-1}^2+(1-\lambda_e)\beta med(A_{e,k}) \quad (15)$$

Where $\beta=1.483(1+\frac{5}{N_w-1})$; $A_{e,k}=\{e_k^2,\cdots,e_{k-N_w+1}^2\}$; λ_e is forgetting factor; $med(\bullet)$ median filter; N_w window length of median filter. Different thresholds T are used to obtain error signal probability distribution of different confidence levels. It is denoted that $\theta_\xi(k)=P\{|e_k|>\xi\}$, $\theta_{\Delta_1}(k)=P\{|e_k|>\Delta_1\}$ and $\theta_{\Delta_2}(k)=P\{|e_k|>\Delta_2\}$. If $\theta_\xi(k)=0.05$, $\theta_{\Delta_1}(k)=0.025$ and $\theta_{\Delta_2}(k)=0.01$, then we will obtain $\xi=1.96\sigma_{e,k}$, $\Delta_1=2.242\sigma_{e,k}$ and $\Delta_2=2.576\sigma_{e,k}$ by calculation. The probabilities are 5%, 95%, 97.5% and 99% when $|e_k|<\zeta$, $\xi\le|e_k|<\Delta_1$, $\Delta_1\le|e_k|<\Delta_2$ and $|e_k|\ge\Delta_2$ [8]. Then S is divided into subspace S_1, S_2, S_3 and S_4.

$$S=S_1\cup S_2\cup S_3\cup S_4 \quad (16)$$

$$S_1=\{(x,d)\in R^N:0\le|d-w^Tx|<\gamma_2\} \quad (17)$$

$$S_2=\{(x,d)\in R^N:\gamma_2\le|d-w^Tx|<\gamma_3\} \quad (18)$$

$$S_3=\{(x,d)\in R^N:\gamma_3\le|d-w^Tx|<\gamma_4\} \quad (19)$$

$$S_4=\{(x,d)\in R^N:\gamma_4\le|d-w^Tx|\} \quad (20)$$

Where $\gamma_2=\xi=1.96\sigma_{e,k}$; $\gamma_3=\Delta_1=2.242\sigma_{e,k}$; $\gamma_4=\Delta_2=2.576\sigma_{e,k}$. The above equations show that S_1, S_2, S_3 and S_4 represent data pairs (x,d) with output error ranges in $[0,\gamma_2)$, $[\gamma_2,\gamma_3)$, $[\gamma_3,\gamma_4)$ and $[\gamma_4,\infty)$. Impulse-free noise disturbance data pairs (x,d) are 95%, 2.5%, 1.3% and 1.2% in subspace S_1, S_2, S_3 and S_4 by Gaussian signal probability distribution. If $(x_k,d_k)\in S_1$, $(x_k,d_k)\in S_2$, $(x_k,d_k)\in S_3$ and $(x_k,d_k)\in S_4$, then H_{k1}, H_{k2}, H_{k3} and H_{k4} will denote collections of coefficient vectors w satisfying $|d_k-w_k^Tx_k|\le\gamma_1$, $|d_k-w_k^Tx_k|\le\gamma_2$, $|d_k-w_k^Tx_k|\le\gamma_3$ and $|d_k-w_k^Tx_k|\le\gamma_4$ at k moment.

$$H_k=H_{k1}\cup H_{k2}\cup H_{k3}\cup H_{k4} \quad (21)$$

$$H_{kp}=\{w\in R^N:|d_k-w_k^Tx_k|\le\gamma_p,(x_k,d_k)\in S_p\} \quad p=1,2,3,4 \quad (22)$$

In ISM-SCMPNLMS algorithm, filter coefficient will be conducted with iterative update only when $w\notin H_k$, thus effectively decreasing iterations. The minimum disturbance principle derives the target of algorithm as follows. In iteration process, the weight vector of adaptive filter changes to the minimum under the restrain of updated filter output. The following constrained optimization problems are solved.

$$\min\|w_{k+1}-w_k\|^2_{Q_{k+1}^{-1}} \quad (23)$$

According to set-membership theory, w_k will evolved to the border of H_{k1}, H_{k2}, H_{k3} and H_{k4} when $w\notin H_k$. Therefore, constraint optimization problems should satisfy the following conditions.

$$d_k-w_{k+1}^Tx_k=\begin{cases}\gamma_1 & if\ (x_k,d_k)\in S_1\\ \gamma_2 & if\ (x_k,d_k)\in S_2\\ \gamma_3 & if\ (x_k,d_k)\in S_3\\ \gamma_4 & if\ (x_k,d_k)\in S_4\end{cases} \quad (24)$$

Using Lagrange multiplier method, the following problems can be solved to obtain a set of unconstrained minimization function.

$$F_p[w_{k+1}]=\|w_{k+1}-w_k\|^2_{Q_{k+1}^{-1}}+\lambda_p\left(d_k-x_k^Tw_{k+1}-\gamma_p\right),p=1,2,3,4 \quad (25)$$

Where λp is Lagrange multiplier and p=1, 2, 3, 4. It is denoted that gradient of $F_p[w_{k+1}]$ is zero.

$$w_{k+1} = w_k + \frac{\lambda_p}{2} Q_{k+1} x_k \quad (26)$$

Constraint condition equation (24) is substituted into Equation (26).

$$\frac{\lambda_p}{2} x_k^T Q_{k+1} x_k = d_k - x_k^T w_k - \gamma_p = e_k - \gamma_p \quad (27)$$

$$\frac{\lambda_p}{2} = \frac{e_k - \gamma_p}{x_k^T Q_{k+1} x_k} \quad (28)$$

Equation (28) is substituted into Equation (26).

$$w_{k+1} = w_k + \frac{Q_{k+1} x_k}{x_k^T Q_{k+1} x_k}(e_k - \gamma_p) \quad (29)$$

Regularization parameter δ is introduced into Equation (29) to derive coefficient update equation of ISM-SCMPNLMS algorithm.

$$w_{k+1} = w_k + \alpha_k \frac{Q_{k+1} x_k e_k}{\delta + x_k^T Q_{k+1} x_k} \quad (30)$$

Where

$$a_k = \begin{cases} 1 - \gamma_1/|e_k| & if\ \gamma_1 < |e_k| < \gamma_2 \\ 1 - \gamma_2/|e_k| & if\ \gamma_2 < |e_k| < \gamma_3 \\ 1 - \gamma_3/|e_k| & if\ \gamma_3 < |e_k| < \gamma_4 \\ 1 - \gamma_4/|e_k| & if\ \gamma_4 < |e_k| \\ 0 & else \end{cases} \quad (31)$$

Adaptive filter coefficient update process indicates that error signal is large in the initial stage of the algorithm and $\sigma_{ek} \gg \sigma_{vk}$. The calculated mode of γ_1 and γ_2 shows that $\gamma_2 \gg \gamma_1$. The coefficient is updated in subspace S_1. $\gamma_1/|e_k|$ is a small positive number. Therefore, a_k is a positive number close to 1. The algorithm can converge quickly. If filter converges to steady state and there is no impulse noise, then $\sigma_{ek} \approx \sigma_{vk}$; $\gamma_2 < \gamma_1$; $a_k = 0$. Therefore, the update time of filter coefficient is reduced. If the filter converges to steady state and there exists impulse noise, then $|e_k|$ will suddenly increase. The coefficient is updated in subspace S_2, S_3 and S_4. If $|e_k|$ is equal to γ_2, γ_3 or γ_4, then $w \in H_k$; $a_k = 0$. The filter coefficient is not updated. Otherwise, a_k will be selected from $1 - \gamma_2/|e_k|$, $1 - \gamma_3/|e_k|$ or $1 - \gamma_4/|e_k|$. Therefore, if the filter converges to steady state and there is impulse noise disturbance, then the range of a_k will be $[0, 0.13)$. The algorithm instability problems can be solved.

4. Simulation analysis

ISM-SCMPNLMS is applied in echo elimination to test effectiveness of the algorithm. Firstly, the method in Reference [8] is used to generate sparse echo path with impulse response length of 256 in Figure 1. The adaptive filter order L is equal to channel sparse echo path length. Secondly, the true voice with sampling frequency of 8 kHz is taken as input signal to compare the above algorithm with SCMPNLMS and SM-SCMPNLMS in References [2] and [3]. In SCMPNLMS algorithm, the step is 0.3. In SM-SCMPNLMS algorithm, error threshold $\gamma_1 = \sqrt{5}\sigma_n$. After passing through echo path, input signal is added with Gauss white noise n_k to obtain expectation signal. Impulse noise $v(k)$ is iterated at the positions $\frac{2K}{5}$, $\frac{3K}{5}$ and $\frac{4K}{5}$, where K is the length of input data. At last, normalized misalignment is taken as performance evaluation index. It is defined as follows.

$$10\log_{10} \|\varpi - w_k\|_2^2 / \|\varpi\|_2^2 \quad (32)$$

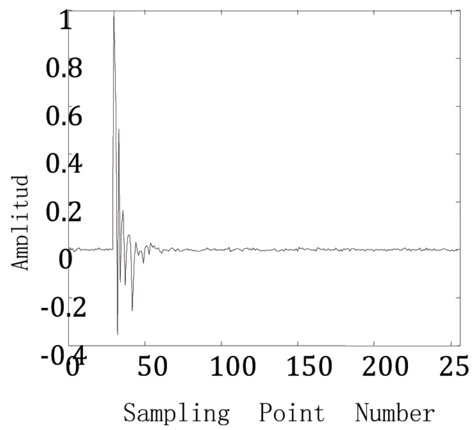

Figure 1. Impulse response of sparse echo path

Algorithm convergence performance comparison based on true voice input is researched by simulation experiment.

Figure 2. shows normalized misalignment performance of new and related algorithms based on true voice input. The SNR is 35dB. There exists large impulse noise disturbance where $k = 2 \times 10^5$; $k = 3 \times 10^5$; $k = 4 \times 10^5$. In Figure 2, there is no impulse noise disturbance at the early stage. ISM-SCMPNLMS algorithm proposed in the work has familiar performance with SCMPNLMS and SM-SCMPNLMS algorithms. Large impulse noise emerges at the steady stage. SCMPNLMS and SM-SCMPNLMS algorithms have poor output performance in weight updating and filtering solution. However, ISM-SCMPNLMS algorithm does not

update or updates filter coefficient by little step. The computation complexity was reduced to improve steady-state performance by restraining error signal amplitude and using larger error threshold.

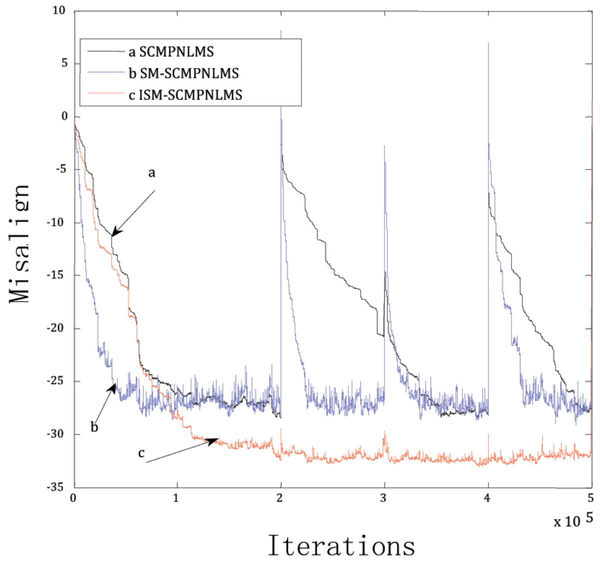

Figure 2. Performance comparisons of algorithms based on true voice

5. Conclusions

In the work, the data collection of "input-expectation" was divided into four data space by ISM-SCMPNLMS algorithm. The data space with small data ratio was calculated by SM-SCMPNLMS Algorithm. In data space with large data ratio, the computation complexity was reduced to solve steady-state problems because of pulse noise disturbance by restraining error signal amplitude and using larger error threshold. Simulation results show that the new algorithm can effectively restrain large impulse noise disturbance compared with SM-SCMPNLMS algorithm in the same convergence rate.

Acknowledgements

The work was supported by PAPA and its Application Based on Sparse Impulse Response, Key Science and Technology Research Project in Colleges and Universities in Guangxi Province (Gran No. [2014] 8, Project No. ZD2014133).

References

1. Hongyang Deng, Milo˘s Doroslova˘cki: Improving Convergence of the PNLMS Algorithm for Sparse Impulse Response Identification, IEEE SIGNAL PROCESSING LETTERS, 2005,12(3): 181-184.
2. Pradeep Loganathan, Andy W.H. Khong, Patrick A. Naylor: A Class of Sparseness-Controlled Algorithms for Echo Cancellation, IEEE SIGNAL PROCESSING LETTERS, 2009,17(8): 1591-1601.
3. Wu Bin, Hou Chulin: A Low Complexity Sparse Controlled MPNLMS Algorithm, Computer Engineering and Applications, 2013, 49(19): 227-231.
4. Y. Zou, S. C. Chan: Recursive Least M-estimate (RLM) adaptive filter for robust filtering in impulse noise, IEEE SIGNAL PROCESSING LETTERS, 2000,7(11): 324-326.
5. M. Bhotto, A. Antoniou: A robust set-membership normalized least mean-square adaptive filter, Proc. IEEE Can. Conf. Elect. Comput. Eng., May 2010: 1–5.
6. M. Z. A. Bhotto, A. Antoniou.: Robust quasi-Newton adaptive filtering algorithms, IEEE Trans. Circuits Syst. II, Exp. Briefs, 2011,58(8): 537-541.
7. Sheng Zhang, Jiashu Zhang: Set-Membership NLMS Algorithm With Robust Error Bound, IEEE Trans. Circuits Syst. II, Exp. Briefs, 2014,61(7): 536-540.
8. Andy W.H. Khong, Patrick A. Naylor: Efficient Use of Sparse Adaptive Filters, Signals system and computers. ACSSC'06: 1375-1379.